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Employing multi-modal sensors for personalised smart home health monitoring.

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Employing Multi-Modal Sensors for Personalised Smart Home Health Monitoring

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Abstract. As the prevalence of IoT sensor equipment in smart homes continues to rise, long term monitoring for personalised and more representative health tracking has become more accessible. The estimation of physiological health factors such as gait and heart rate can be captured using a range of diverse sensor equipment, while behavioural changes are now being monitored using simple binary sensors through activity classification and profiling. Combining both physiological and behavioural monitoring in fixed layout properties has already allowed us to effectively consider fall risk. However, expanding application of the system to new layouts and conditions requires consideration of differing retrofit home layouts and sensor configurations. A wider selection of sensors in varying configurations could potentially allow for the identification of other health conditions such as heart disease and stroke.

Key words: Smart Homes · Sensors · Time-series Data · Human Activity Recognition · Long Term Health Monitoring

1 Introduction

Scotland and the UK are facing an aging population, as people live longer. 10 million people in the UK are currently over 65 years with a 5.5 million increase projected over the next 20 years. 3 million people are aged over 80 and the number is expected to double by 2030. This puts additional strains on the health and social services with both a smaller proportion of the population of working age available to support the service, and with the older population tending to have more complex medical needs. Furthermore, with modern lifestyles carers from within the family are less available. Generally, more people are tending to live alone and families are tending to live further apart as people are more likely to relocation for work or education either within the UK or internationally. In this changing scenario it is important that we help people with medical or social needs to live independently for longer and so reduce their reliance on more expensive health care solutions.

Smart Homes and accompanying IoT (Internet of Things) devices have become increasingly popular under the premise of home automation and security.

This recent push for wider acceptance of ubiquitous sensor devices in smart home environments provides a unique opportunity to perform long term monitoring of health in the home environment. While ongoing health conditions such as dementia and fall risk are typically diagnosed, monitored and addressed in hospital environments, the measurements taken in these tests can potentially be performative, and so not as representative of natural measurements. Additionally, performing tests in hospital environments can be expensive and difficult to access for remote communities or people with reduced mobility. By utilising smart home sensor networks to monitor resident behaviour and physiological expressions, the risk factors typically identified only through hospital testing can be monitored in casual home environments.

In prior work, a primarily rule-based system was designed and implemented to perform fall risk determination in a real smart home sensor environment. FitHomes is a social housing project lead by Albyn Housing Society Ltd focused on improving conditions and fostering independence for residents living with mobility issues. 16 purpose-built homes have been constructed at Dalmore near Invergordon in the UK; and an additional development of a further 32 homes is currently planned. FITsense is a data analysis system which uses human activity recognition to produce daily resident profiles in FitHome installations. A rule-based segmentation system is used to break long sequences of sensor activations down into smaller windows, upon which a rule-based activity classifier was used to identify ADLs (Activities of Daily Living). The instance and regularity of ADL expressions is used to produce ratings for an overall profile of potential fall risk, considering factors such as sedentary time, bathroom usage and overall sleep time. These profiles are then be graphed over a given period of time to flag significant changes in relevant factors.

As additional FitHome installations are planned, challenges have arisen in expanding the existing FITsense system. The current rule-based systems require extensive domain knowledge with respect to the sensor configuration and layout in order to produce robust compatible rules, while the underlying work in generating rules for each additional unique layout is very time-consuming. Additionally, attempting to support flexible sensor configurations in variable house layouts increases the complexity and granularity of ADLs which can be captured and so increases the complexity of the rules required.

This project aims to address key issues facing the expansion of the FitHomes network, the FITsense system and its overall capabilities. By transitioning from a rule-based approach to ADL classification to a sustainable ML-based approach, the FITsense system needs to scale efficiently as the FitHomes network grows, especially to retrofit home environments where unique configurations and layouts will be commonplace. There may also be opportunities to introduce additional sensors to improve the behavioural modelling and physiological monitoring capabilities of the sensor network.

2 Related Work

Long term monitoring in home environments has been a constantly evolving field due to the large range of pervasive sensor technologies being used, such as infrared motion sensors and wearable accelerometers. A relatively simple and high impact form of health monitoring in home environments is fall detection. Fall detection is a well-developed area of research, with many iterative solutions providing consistent strong performance [1]. While functional solutions for fall detection have impressive impact, the problem has been approached using a variety of sensor technologies. It has largely been decided that the implementation requirements, such as how permissive residents are to relatively invasive technologies, are the limiting factors for the performance of such a system, rather than the underlying algorithms [2]. Fall prediction is a more challenging form of long term monitoring with traditional hospital testing typically relying on gait measurements to infer potential fall risk. Accurate physiological monitoring provides a key advantage in this area with some successful fall prediction systems efficiently using similar measurements [3]. However an underused area in this field is behavioural modelling, through the observation of sequential resident movements and behaviours. Modelling regular behaviours and their relation to physiological expressions such as bathroom usage and dehydration, as well as the relationship between abberant behaviour and long term mental conditions such as dementia could potentially highlight health conditions well before they would typically be identified in hospital conditions [4].

3 Key Challenges

3.1 Sustainable ADL Classification

The task of ADL classification from smart home sensor data can be split into two main areas: sequence windowing, by which long sequences of sensor activations are segmented into shorter sequences representative of an activity, and activity recognition, in which those sequences can then assigned an activity label. While the FITsense system works well as a proof-of-concept in the current FitHomes installation, it relies heavily on a rule-based approach to sequence windowing and activity classification. This was originally selected during development as only detailed domain knowledge on the house layout and sensor configuration were available. As there was no reliance on manually labelled sensor data, which would be required by a supervised model, development could progress alongside construction.

The initial FitHomes houses make use of a reference layout which is almost identical across all houses. However, as the FitHomes project expands to new environments including new constructions and existing retrofit homes, additional intercompatible rulesets must be produced for each unique environment added to the sensor network. As more rules are added to the system it becomes more difficult to ensure effective conflict resolution. As the overall supply of FitHomes data becomes more consistent and the work required to maintain the existing rule-based implementation increases, it has become clear that a data-driven ML-based approach to ADL classification would be a more sustainable method of supporting the expansion of the FitHomes network.

The challenges in producing a rule-based classifier stem from the requirement for extensive domain knowledge and the expense in producing a ruleset. However in developing an ML-based system, the key challenges are the acquisition of labelled training data and designing the representation used in the model. Few publicly available smart home activity recognition datasets exist, largely due to the cost and human involvement required in their production [5]. In practice, it was found in the FitHomes project that residents were most receptive to paper-based journalling over a 24 hour period. More training examples are required to produce a large enough dataset to train a deep model such an LSTM. An experimental form of manual bootstrapping is currently being performed by collecting the surrounding 13 days of unlabelled data from a resident's home and using their paper journal as a template for their behaviours and movements around the home in the manual labelling process. This compromise between data cost and quality requires further research to identify its effect on the overall performance and scalability of an ML-based classifier and would be a useful area in which to receieve guidance.

3.2 Using Additional Sensors

The majority of sensor equipment used in the FitHomes network is comprised of simple infrared motion sensors producing binary activation data. The FIT-sense system is designed to extract behavioural information from movement and activity in each home, with sequential behaviour tracking capturing temporal dependencies between relevant activities. However, this coarse data stream limits the complexity of tracked activities. The pending expansion of the FitHomes network provides an opportunity to research additional sensor equipment which may be used to improve the behavioural and physiological monitoring capabilities of the FITsense system.

RF-based sensor technologies are becoming increasingly relevant due to their unintrusive nature [6]. Among the most useful demonstrated capabilities are indoor localisation, and heart and breathing rate estimation. However the high-end equipment required to implement such solutions restrict their accessibility for ubiquitous deployment. An alternative hardware solution involves using commodity WiFi devices as a rudimentary Tx/Rx software defined radio, through observation of CSI (Channel State Information). While commodity devices offer reduced control relative to enterprise-grade RF equipment, CSI-based solutions have shown promise in physiological and behavioural monitoring tasks [7].

Many current approaches to CSI-based physiological monitoring solutions take a signal processing approach rather than using ML methods. This has been shown to be successful with careful and time-consuming selection and preprocessing of relevant subcarrier signals, however it is possible a privileged learner could be trained to perform this task. I am seeking to learn more about data preprocessing for an ML-based solution, how it would factor in and whether it may offer better performance than current state of the art.

3.3 Monitoring Additional Health Conditions

Researching risk factors for fall risk determination through both literature and discussion with healthcare professionals highlighted other conditions which could be diagnosed using similar methods. However establishing thresholds of risk factors which are both representative of medically significant metrics and personalised to suit the subject is a challenging task. The current thresholds used are produced through comparison to those found in hospital testing, however this does not factor in personalisation to residents and their specific demographics.

Case-based reasoning could potentially have an application in the generation and comparison of resident behaviour profiles. I am seeking guidance in how initial risky prototype cases could be generated to populate the initial case base. A similarity metric for related risky behaviours and resident profiles will also require consideration.

Another area in which I am seeking guidance is my approach to the selection of health conditions for which to develop monitoring profiles, and whether it should be informed by the additional sensors added to the network, or vice versa.

4 Current Progress

My research methodology is still developing as the current literature is being reviewed. A review of pertinent sensor data analysis and fall risk determination procedures was published in 2019 [5].

Using FitHomes data, initial research outlining the effect of highlighting existing temporal dependencies in sensor data sequences for ADL classification has been performed. This has shown promise in improving the performance of LSTM classifiers across a range of smart home datasets.

Preliminary data gathering using a rudimentary CSI collection setup has been performed, with several tools being developed to facilitate the preprocessing of generated data for realtime analysis.

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